Rewarding Coreference Resolvers for Being Consistent with World Knowledge

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Rewarding Coreference Resolvers for Being Consistent with World Knowledge

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Abstract

Unresolved coreference is a bottleneck for relation extraction, and high-quality coreference resolvers may produce an output that makes it a lot easier to extract knowledge triples. We show how to improve coreference resolvers by forwarding their input to a relation extraction system and reward the resolvers for producing triples that are found in knowledge bases. Since relation extraction systems can rely on different forms of supervision and be biased in different ways, we obtain the best performance, improving over the state of the art, using multi-task reinforcement learning.

1 Introduction

Coreference annotations are costly and difficult to obtain, since trained annotators with sufficient world knowledge are necessary for reliable annotations. This paper presents a way to simulate annotators using reinforcement learning. To motivate our approach, we rely on the following example from Martschat and Strube (2014, colors added to mark entity mentions):

(1) [\textit{Lynyrd Skynyrd}]\(^1\) was formed in \textit{Florida}.\(^2\)

Other bands from \textit{the Sunshine State}\(^2\) include \textit{Fireflight} and \textit{Marilyn Manson}.

Martschat and Strube (2014) cite the association between \textit{Florida} and \textit{the Sunshine State} as an example of a common source of name-name recall error for state-of-the-art coreference resolution systems. The challenge is that the two names co-occur relatively infrequently and are unlikely to do so in a moderate-sized, manually annotated training corpus. A state-of-the-art system may be able to infer the relation using distributional information about the phrase \textit{the Sunshine State}, but is likely to have limited evidence for the decision that it is coreferential with \textit{Florida} rather than \textit{Lynyrd Skynyrd}.

While coreference-annotated data is scarce, knowledge bases including factual information (such as that \textit{Fireflight} is from \textit{Florida}) are increasingly available. For a human annotator unaware that \textit{Florida} is sometimes referred to as \textit{the Sunshine State}, the information that \textit{Fireflight} is from \textit{Florida} is sufficient to establish that \textit{Florida} and \textit{the Sunshine State} are (with high probability) coreferential. This paper explores a novel architecture for making use of such information from knowledge bases by tying a coreference resolution system to a relation extraction system, enabling us to reward the coreference system for making predictions that lead us to infer facts that are consistent with such knowledge bases. This potentially provides us with more evidence for resolving coreference such as (1).

We propose a training strategy (Figure 1) in which we pass on the predictions of a neural coreference resolver to an open relation extraction (OpenRE) system, matching relations extracted from resolved sentences with a knowledge base. We show how checking the produced relationships for consistency against the knowledge base produces a reward that is, indirectly, a signal about the quality of the coreference resolution. In order to generalize this signal beyond the coverage of the knowledge base, we train a Universal Schema model (Riedel et al., 2013) and use its confidence as our reward function. With this reward function,
we do policy-gradient fine-tuning of our coreference resolver, effectively optimizing its predictions’ consistency with world knowledge.

**Contributions** We demonstrate that training a coreference resolver by reinforcement learning with rewards from a relation extraction system, results in improvements for coreference resolution. Our code is made publicly available at [https://github.com/rahular/coref-rl](https://github.com/rahular/coref-rl)

## 2 Consistency Reward for Coreference Resolution

In order to reward a coreference resolver for being consistent with world knowledge, we propose a simple training strategy based on relation extraction: (i) Sample a Wikipedia document at random, (ii) Replace mentions with their antecedents using a coreference resolver, (iii) Apply an off-the-shelf openRE system to each rewritten document, (iv) Score relationships that include coreferent mentions using Universal Schema, and (v) Use the score as a reward for training the coreference resolvers.

**Reward functions** To model consistency with world knowledge, we train different Universal Schema models ([Riedel et al., 2013; Verga and McCallum, 2016]), resulting in three reward functions (Figure 2): **RE-KG** (Knowledge Graph Universal Schema) is trained to predict whether two entities are linked in Wikidata; **RE-Text** (Text-based Universal Schema) is trained to predict whether two entities co-occur in Wikipedia; and **RE-Joint** (Joint Universal Schema) is trained to predict whether two entities are linked and co-occur. The three rewards focus on different aspects of relationships between entities, giving complimentary views of what entities are related.

Similar to Verga et al. (2016), we parameterize candidate relation phrases with a BiLSTM ([Graves and Schmidhuber, 2005]), and use pre-trained Wikidata BigGraph embeddings ([Lerer et al., 2019]) as the entity representations. We apply a one-layer MLP on the concatenated representations to get the reward value.

**Updating the coreference resolver** Each resolved document is converted into $n$ subject-relation-object (SRO) triples by an open information retrieval system ([Angeli et al., 2015]). Each triple $t_i$ is then scored using a reward function to obtain a reward $r_i$ for $i \in \{1, \ldots, n\}$. The final document-level reward is the normalized sum of the individual rewards as shown in Equation 1, where $R_h$ is a moving window containing the previous $h = 100$ normalized reward values.

$$R = \frac{\sum_i r_i - mean(R_h)}{stddev(R_h)} \quad (1)$$

Since $R$ is not differentiable with respect to the coreference resolver’s parameters, we use pol-
3 Experiments

We use a state-of-the-art neural coreference resolution model (Lee et al., 2018) as our baseline coreference resolver. This model extends Lee et al. (2017) with coarse-to-fine inference and ELMo pretrained embeddings (Peters et al., 2018).
Table 2: Coreference results: average F1 scores on the OntoNotes and WikiCoref test sets. Differences are significant w.r.t. $B^3$ (bootstrap test, $p < 0.05$).

Better linking As a direct consequence of the above, the model is inclined to also link noun phrases that are not entities. In the second example of Figure 3, we see that “This attempt” is linked to “releasing” by the fine-tuned model. Interestingly, we do not see this type of eventive noun phrase linking either in OntoNotes or in the predictions of the baseline model.

This phenomenon, however, also has a side-effect of producing singleton clusters and spurious linking, which adversely affect the recall. On the OntoNotes test data, while the average precision of the best performing fine-tuned model is higher than the baseline (75.62 vs. 73.80), a drop in recall (70.75 vs. 71.34) causes the final F1 score to only marginally improve.

6 Related Work

Coreference resolution Among neural coreference resolvers (Wu and Ma, 2017; Meng and Rumshisky, 2018), Lee et al. (2017) were the first to propose an end-to-end resolver which did not rely on hand-crafted rules or a syntactic parser. Extending this work, Lee et al. (2018) introduced a novel attention mechanism for iteratively ranking spans of candidate coreferent mentions, thereby improving the identification of long distance coreference chains. Zhang et al. (2019) improve pronoun coreference resolution by 2.2 F1 using linguistic features (gender, animacy and plurality) and a frequency based predicate-argument selection preference as external knowledge. Emami et al. (2018) incorporate knowledge into coreference resolution by means of information retrieval, finding sentences that are syntactically similar to a given instance, and improving F1 by 0.16.

Reinforcement learning RL has been used for many NLP tasks, including coreference resolution (Clark and Manning, 2016) and relation extraction (Zeng et al., 2018). Clark and Manning (2016) use RL to improve coreference resolution by optimizing their mention ranking model and directly use the standard evaluation metrics as the rewards. We, on the other hand, perform end-to-end optimization by rewarding the model’s consistency with real world knowledge using relation extraction. To our knowledge, we are the first to use consistency with world knowledge as a reward for
tasks other than knowledge base construction.

Knowledge bases Knowledge bases have been leveraged across multiple tasks across NLP (Bordes et al., 2011; Chang et al., 2014; Lin et al., 2015; Toutanova et al., 2015; Yang and Mitchell, 2017). Specifically for coreference resolution, Prokofyev et al. (2015) implement a resolver that ensures semantic relatedness of resulting coreference clusters by leveraging Semantic Web annotations. Their work incorporates knowledge graph information only in the final stage of the resolver’s pipeline, and not during training. In contrast, our work augments information from the knowledge base directly into the training pipeline. Also, they use DBpedia (Auer et al., 2007) as the ontology. Although both Wikidata and DBpedia are designed to support working with Wikipedia articles, DBpedia can be considered as a subset of Wikidata as Wikipedia infoboxes are its main data source. The advantage of Wikidata over DBpedia is its size, and the fact that it is multilingual, which will allow applying our method to other languages in the future.

7 Conclusion

We presented an architecture for adapting coreference resolvers by rewarding them for being consistent with world knowledge. Using simple multi-task reinforcement learning and a knowledge extraction pipeline, we achieved improvements over the state of the art across two datasets. We believe this is an important first step in exploring the usefulness of knowledge bases in the context of coreference resolution and other discourse-level phenomena. In this area, manually annotated data is particularly expensive, and we believe leveraging knowledge bases will eventually reduce the need for manual annotation.

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